The Measurement and Determinants of Skill Acquisition in Young Workers' First Job

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Abstract

We analyse participation in five types of training (formal on-site, formal off-site, informal co-worker training, learning by watching and learning by doing) and self-assessed skill acquisition in young Flemish workers' first job. A skill production function is estimated whereby the simultaneity of participation in the different types of training and skill acquisition is taken into account. Our results clearly demonstrate the importance of informal training. Formal training participation is found to be only a fraction of total training participation. Moreover, the determinants of total training participation and skill acquisition differ from those of formal training participation. While some training types are complementary, others are clearly substitutes. Finally, most types of training generate additional skills. Nonetheless, learning by doing is found to be complementary to formal education in the production of both specific and general skills, whereas formal training serves as a substitute.

Keywords: human capital, training, OJT, school leavers, first job

I. Introduction

The policy debate about education and schooling is increasingly focused on the importance of life-long learning and the acquisition of post-school skills. Employee training is seen as crucial both for the individual worker's successful career in the labour market and for the competitiveness of the individual firm and the economy as a whole. This increased interest follows decades of both theoretical and empirical research on the economics of training. For a long time, research has been hindered by a lack of suitable data on participation in on-the-job training (OJT). Instead, early empirical contributions to this issue relied on indirect measures such as tenure and work experience (see, e.g., Mincer, 1974). Motivation for the use of these indirect measures is based on neoclassical Human Capital theory. In general, the optimal pattern of investment in skills is to continue investment but at a declining level over the individual's working life (Ben-Porath, 1967; Mincer, 1974). The availability of OJT indicators in more recent data sets has delivered the opportunity to more directly test their relationship with other variables of interest, such as wages and turnover, and to fill some research gaps. A large part of this literature has contributed to the analysis of the determinants of participation in OJT and delivered substantial evidence that there are great differences in training opportunities between particular groups of workers.

Training participation measures, however, also have serious flaws. The following problems are apparent when the incidence and determinants of OJT and post-school skill acquisition are analysed. First, training indicators often fail to incorporate more informal ways of skill acquisition such as learning by watching or learning by doing (Sicherman, 1990). As shown by Mincer (1989) and Barron et al. (1997), formal training participation seems to represent only a fraction of total training participation. Hence, incorrect conclusions will be drawn if more informal training offsets lower formal training participation. Second, training only measures skill formation in an indirect way through the time invested in skill formation, but it does not incorporate the intensity and efficiency of the skill formation process. Some workers will need less training time than others to acquire the same skills. Furthermore, some training types may be more efficient than others. In response to these flaws, a growing amount of literature focuses on the measurement of skills and the use of alternative skills measures in economic analysis (see, e.g., Borghans et al., 2001). Third, training indicators do not discriminate between different kinds of skills. However, the distinction between general and specific skills is crucial in the analysis of investments in training (see Becker, 1964). From the worker's perspective, general or transferable skills are clearly preferable, since they raise wages for the current job and enhance outside labour market opportunities.

The purpose of this paper is to examine the consequences of these problems for the analysis of the determinants of training participation and on-the-job skill acquisition. We address these problems using survey data on entry-level jobs in Flanders. The data deliver substantial information on almost all types of formal and informal OJT participation: (1) formal off-site training, (2) formal on-site training, (3) informal training by a co-worker or supervisor, (4) learning by watching, and (5) learning by doing. Furthermore, respondents were asked to describe assess their skill acquisition during their first job and to gauge the transferability of these skills. Although our decision to focus on first jobs is primarily based on data-availability considerations, it is an interesting focus in its own right, since investments in OJT are likely to be more prevalent at the start of the labour market career. Moreover, as labour market segmentation theories suggest, a bad start might have strong adverse consequences for the rest of one's career. Four specific issues are investigated. First, we assess the quantitative importance of participation in informal training and self-reported skill acquisition in young workers' first job in comparison with participation in formal OJT courses. Second, the determinants of the different types of formal and informal training are analysed. We compare the results and examine whether the different types of training are complements or substitutes. Third, the determinants of skill acquisition and its transferability are investigated and compared with those of OJT. Fourth, the impact of the different types of training on skill acquisition and its transferability is analysed. Such an investigation allows us to identify the most efficient training activities in the production of skills and enables us to assess the appropriateness of the different training variables as indicators of skill acquisition.

The article is structured as follows: section II focuses on the theoretical framework and gives an overview of the existing evidence regarding the determinants of training participation. The data and empirical model are described in section III. In section IV, we analyse the determinants of the different types of OJT. Section V explores the determinants of skill acquisition and the extent to which differences in skill acquisition result from differences in training participation. Finally, in section VI, we summarise the paper and draw some general conclusions.

II. Theoretical Framework and Existing Evidence

We assume that the volume of on-the-job training of worker *i*, $\mathbf{OJT_i}$, can be decomposed into the volume of *n* different training types *t* such as formal off-site training, formal on-site training, informal training by a co-worker or supervisor, learning by watching, and learning by doing. Following earlier theoretical and empirical research on OJT, we further assume that the amount of each individual type of training OJT_{ti} is a function of those factors that influence the expected return on the training investment. Factors that influence this return might be observed factors $\mathbf{X_i^{t1}}$, such as the educational background, gender or the type of contract, and unobserved residual characteristics ε_i^{t1} like motivation, ambition or ability:

$$(1.1) \qquad OJT_{ti} = f_t^1\left(\mathbf{X_i^{t1}}, \varepsilon_i^{t1}\right)$$

These volumes of training in turn serve as input factors for the on-the-job acquisition of skills SA_i. A similar amount of training of type *t* should not lead to the same amount of skill acquisition, as workers might differ in their relative learning productivity. This learning productivity might depend on observed individual characteristics $\mathbf{X_i^2}$, like level of education, and unobserved characteristics ε_i^2, like ability. As a result, we construct the following skill production function:

$$(1.2) \qquad SA_i = f_t^2\left(\mathbf{OJT(X_i^1, \boldsymbol{\varepsilon}_i^1)}, \mathbf{X_i^2}, \varepsilon_i^2\right)$$

Finally, by the grouping of the relevant observed characteristics into $\mathbf{X_i^3} = \left[\mathbf{X_i^1}, \mathbf{X_i^2}\right]$, we can also specify the following reduced form equation:

$$(1.3) \qquad SA_i = f_t^3\left(\mathbf{X_i^3}, \varepsilon_i^3\right)$$

Several conclusions can be drawn from the large number of studies that have analysed the determinants of OJT (cf. equation (1.1)). All of them have theoretical foundations, which also apply to the determinants of skill acquisition. The robustness of these findings for each separate type of training and for skill acquisition will be tested in the empirical analysis.

A logical indicator for the learning productivity of the worker is his or her educational attainment. Hence, we expect that skill acquisition is positively related to the educational level of the worker. Support for the higher trainability of higher-educated workers can be found in several theoretical contributions. Arrow (1973a) and Spence (1973) argue in their signal theories that the non-pecuniary costs of formal education are lower for more able students. We can suppose that this is also the case with respect to post-school skill acquisition. Thurow (1975) also states that the educational level of the worker serves as a signal of trainability. Other authors, such as Rosen (1976), argue that formal education in itself may enhance the efficiency of the skill formation process. Altonji and Spletzer (1991) as well as Veum (1997) have found an effect on training participation from both educational level and ability-oriented test scores. The expected positive impact of educational attainment on participation in OJT has also been confirmed by a large number of other empirical studies (Greenhalgh and Stewart, 1987; Booth, 1991; Green, 1993; Oosterbeek, 1996; Arulampalam and Booth, 1998, 2001; OECD, 1999; Brunello, 2004; Verhaest and Omey, 2002; Arulampalam et al., 2004).

Women are more likely to quit or interrupt their job, which makes investment in their training less profitable. For young female job applicants, interruptions for pregnancy or maternity might be anticipated. Although not every woman will take a career break, statistical discrimination theories (Phelps, 1972; Arrow, 1973b) state that employers will use the sex of the worker as a signal of the profitability of the training investment (Barron et al., 1993). Several studies have indeed found instances of women participating less in OJT (Greenhalgh and Stewart, 1987; Booth, 1991; Lynch, 1992; Green, 1993; Verhaest and Omey, 2002; Groot and Maassen van den Brink, 2003). Many of the more recent studies could not confirm this result (Veum, 1996; Oosterbeek, 1996; OECD, 1999; Arulampalam et al., 2004), while Altonji and Spletzer (1991) could only find an effect on the total volume of training. The results of Oosterbeek (1998), however, indicated that these equal probabilities resulted from two opposite effects. The shorter supply of company training for women was compensated for by their higher demand for training. Another interesting result was found by Royalty (1996), who, noticing higher OJT probabilities among men, has found that this difference falls by 25% when one controls for predicted turnover. Moreover, her findings have also suggested that training differences by level of education result from differences in predicted turnover.

The expected benefits of investment in training are also lower for part-time and temporary contract workers, since they produce returns over a shorter working period. As regards temporary contract workers, the distinction between fixed-term contract workers and seasonal/casual temporary jobs is relevant (Booth et al, 2002). Fixed-term contracts may be used as a probationary device; if the worker performs very well, for example, s/he may be offered a permanent contract later on. Hence, Booth et al. (2002) have found lower training probabilities for both workers with fixed-term contracts and those with casual or seasonal jobs, with the negative effect of casual and seasonal jobs being much greater than that of fixed-term jobs. Other evidence of lower training participation among flexible contract workers has been adduced by, for example, Oosterbeek (1996), Arulampalam and Booth (1998, 2001), Jonker and de Grip (1999), OECD (1999), Arulampalam et al. (2004), and Draca and Green (2004). Forrier and Sels (2003) equally have not found significant differences in training participation between temporary and permanent contract workers in Belgium.

Job characteristics may also play a significant role as determinants of OJT participation. It is generally found that larger firms provide more training opportunities (Barron et al., 1987; Booth, 1991; Arulampalam and Booth, 1998, 2001; Oosterbeek, 1996; OECD, 1999; Goux and Maurin, 2000; Verhaest and Omey, 2002; Draca and Green, 2004). There are several explanations for this outcome. For example, the costs of training provision may be lower due to economies of scale. This enables larger firms to organise their own training courses, while smaller firms depend more on external training services. Not surprisingly, some studies have found an effect of firm size on on-site training but not on off-site training (Green, 1993; Veum, 1997). Additionally, larger firms have more promotion opportunities, which reduces expected losses from resignations by trained workers. Furthermore, larger firms may have a high degree of monopoly power, which reduces the outside options for workers with industry-specific skills (Groot and Maassen van den Brink, 1998). Workers in the public sector also often participate more in training (Booth, 1991; Arulampalam and Booth, 1998; OECD, 1999; Arulampalam et al., 2004). Since the public sector is not driven by profit maximisation, there is less fear of losses owing to staff turnover. Moreover, utility services such as public transport often have a high degree of monopoly power.

Finally, tenure is also likely to influence training participation. On one hand, training investments can be rented out for a longer period if they are undertaken at the start of the employment relation (cf. supra). On the other hand, imperfect information regarding the turnover probability of the worker might result in delayed training. Hence, we can make the following predictions regarding the relation between tenure and training: first, the total volume of past OJT increases with tenure but at a declining rate. Second, the probability of one's ever having received training during a specific job also increases with tenure but at a declining rate. Third, the probability of participating in training at a particular moment initially increases and then decreases with tenure. This last hypothesis has indeed been confirmed in a study by the OECD (1999), but only for some of the analysed countries. Still, there are some econometric difficulties. First, tenure might be endogenously related to training participation if training influences the mobility behaviour of the worker. Depending on the type of training, this influence can work in both directions. On one hand, specific training increases the worker's attachment to the firm and so will reduce mobility. On the other hand, more general training might enhance a worker's outside options, resulting in a higher quit rate. Second, workers with a higher match quality and thus a lower propensity to quit might have the largest probability of OJT participation. By comparing individuals with similar completed job duration, Loewenstein and Spletzer (1997) found convincing evidence of delayed on-the-job training. Thus, the probability of ever being trained increases with tenure but at a declining rate. After a while, the depreciation of skills could even lead to decreasing skill acquisition.

III. Data and empirical model

A. Data

The empirical research is based on survey data on two cohorts of about 3000 Flemish youngsters, born respectively in 1978 and 1980. At the age of 23, these individuals were questioned about their educational and early labour market careers. The analysis concentrates on their first standard job of at least one hour a week and tenure of at least one month.[1] This job is observed for about 78% of the individuals in the gross sample: a group of 15.5% still studied at the age of 23, while another 6.5% never had a job. An extensive description of the data collection process and general summary statistics can be found in SONAR (2003, 2004). After the exclusion of individuals without first job observation, the self-employed and those with missing values from any of the variables used in the analysis, the final sample was reduced to 4202 respondents. Dealing with the first job, the survey contains extended information on both training participation and skill acquisition. A focus on this job therefore enables the answering of the research questions posed in the introduction. A disadvantage of an analysis on the basis of just one job is the lack of control for individual-specific fixed effects.[2] With respect to other jobs, however, either the detailed information on training participation or the direct measures of skill acquisition are missing. As a result, we follow most of the previous literature on the determinants of training participation and apply a cross-sectional approach.[3]

B. Training participation

Respondents were asked if, during the time of and related to their first job, they participated in one of the following types of training: (1) formal off-site training (TRF-OFS), (2) formal on-site training (TRF-ONS), (3) informal training by a co-worker or supervisor (TRI-CWS), and (4) learning by watching the work of a colleague (TRI-LBW). For formal off-site and on-site training, the number of courses and the duration of each training course were also gathered. No direct questions on learning by doing were asked. Job tenure might be a logical indicator for this type of training. The period over which additional skills are acquired, however, is most likely to be limited and depends on the type of occupation. Occupations in the SONAR database are coded following the Standard Occupational Classification of the Dutch CBS (1992). For each occupation, the CBS provides the minimal number of months that are needed to master the details of the job if the employee has no previous labour market experience and has the necessary educational qualifications. Although assessed by the employer or employee, similar training indicators were used by, for example, Duncan and Hoffman (1979), Barron et al. (1987, 1997), and Sicherman (1990). Still, the period over which the worker still acquires new skills may be much longer than the period that is needed to perform well. Hence, the CBS also provides information on the additional time amount of experience that is needed to qualify for a similar job at a higher level. After that period, the total time of skill acquisition may end, unless one is promoted to the higher-level job. Thus, total volume of learning-by-doing training (TRI-LBD) in the first job is defined as the sum of the period required for optimal performance and the extra period of vocational experience needed to become qualified for a higher-level job. This time period is converted to working weeks, truncated at the total observed working period and corrected for part-time work by the fraction of working time of a full-time worker. For the most elementary occupations (e.g., cleaners), the classification assumes that individuals need less than one month to perform adequately and do not acquire experience that helps them to qualify for a higher job level. Hence, these individuals are considered to have had no learning-by-doing training.

Table 1 describes some summary statistics regarding the various types of training participation. These statistics confirm previous findings that formal training is only a small fraction of total training, when measured by both incidence and volume. About 93% of the young workers in our sample participated in any type of training (TR), while only 23.8% participated in formal training. The most significant types of training in terms of incidence are learning by doing (86.4%) and informal training by a co-worker or supervisor (33.6%). Almost everyone who participated in a formal training course also had some informal training. Similarly, the volume of training through learning by doing is much larger than the total volume of formal training. The disadvantage of the indirect learning-by-doing indicator is that it may overstate the importance of learning by doing if it is partly substituted by other training types. This can only explain part, however, of the much greater figures for learning by doing. About 42% of those with a registered period of learning by doing never had any other type of training, so the lower limit of learning-by-doing incidence is still 36.3%. Similarly, the mean total volume of formal training is only about 4.4% of the mean volume of measured learning-by-doing training. Of course, it is not unlikely that the intensity of TRI-LBD is much lower as it is combined with productive work activities. Another notable finding is the positively skewed distribution of the volume training: a relatively small number of school leavers seem to receive a disproportionately large share of the offered training. Also here, differences in the intensity of the observed training volumes might deliver an explanation. The intensity of the learning-by-doing training, for example, is likely to diminish over time.

“Table 1 here”

For a general indication of the complementarity or substitutability of the different sources of training, simple correlations are computed for each combination of two training participation types (see Table 2).

Although correlations are relatively low, most of the training types seem to be complementary to each other. An exception is informal training by a co-worker or supervisor. This training participation type is negatively correlated with formal on-site training, which suggests that these two types of training are substitutes for each other. Furthermore, TRI-CWS is not correlated with learning by doing or with off-site formal training. Learning by watching and learning by doing are also not correlated with each other. It is therefore likely that the determinants of training are not similar between each type of training.

"Table 2 here"

In the next section, we estimate the determinants of each type of training incidence on the basis of a multivariate probit model (cf. equation (1.1)). We therefore control for the simultaneity of the participation decisions for the different types of training.[4] A bivariate probit model for formal (TRF) and informal (TRI) training types and a univariate probit for any training (TR) incidence are also estimated. Analogously, we estimate the determinants of the volume of TRF-OFS, TR-ONS and TR-LBD, measured in weeks, simultaneously by means of a multivariate Tobit model. Finally, with respect to the number of off-site and on-site formal training courses, we apply a bivariate Poisson regression model.[5] The following explanatory variables ($\mathbf{X}_i^1$) are included as potential determinants of training (1.1): years of education, tenure (in months) and tenure squared, dummies for women (1), non-European descent (1), firm size (3), type of contract (3), part-time jobs (1), public sector (1), white-collar workers (1), industry (11) and region of employment (6). For the type of contract, a distinction is made between permanent contracts (the reference), fixed-term contracts, seasonal or casual jobs, and special employment measure contracts. This last type consists of a wide range of contracts, implemented by policy makers to enhance the entry process of young workers. Generally, these contracts are issued alongside fiscal stimuli for employers.

Given the problems of endogeneity with respect to tenure and tenure squared (cf. supra), we apply the 'two-stage conditional maximum likelihood' procedure proposed by Rivers and Vuong (1988). This procedure estimates the reduced form equations of the endogenous variables (i.e., tenure and tenure squared) by OLS in the first stage. The estimated error terms of these equations are then included as additional explanatory variables in the second-stage probit equation. This procedure has several advantages. First, it is easy to implement, and it can be applied to all kinds of limited dependent variable models.[6]

Second, Rivers and Vuong showed that these estimates are consistent with and at least as efficient as other two-stage approaches such as the simple two-stage instrumental variables probit.[7] Of course, classical maximum likelihood approaches are better alternatives. These approaches, however, often suffer from computational problems in the case of large models.[8] Third, a simple Wald-test on the significance of the probit coefficients of the included error terms delivers an explicit test for exogeneity. For identification purposes, the potential length of the tenure and its square are included as instruments in the first-stage regressions. The individuals in our sample entered the labour market between 1996 and the last months of 2003. At the time of the interview, 40.6% of the respondents were still working in their first job. Hence, the potential length of observed tenure is restricted to the period between the job start date and the time of the interview. This potential length explains to a large extent that observed tenure and is unrelated to the error terms in the training participation equation.

C. Skill Acquisition

A measure for skill acquisition (SA) is derived from the following question in the SONAR-survey: 'In your first job, have you learnt some new skills which you didn't possess before?' For our sample of 4202 school leavers, almost three out of four (72.8%) answered in the affirmative, so not all individuals who participate in some type of training acquire new skills. Nonetheless, the incidence of overall skill acquisition is still far larger than the incidence of formal training participation. Of importance is to what extent the acquired skills are job-specific or general (cf. Table 1). The transferability of the acquired skills can be derived from the question: 'Are these skills of use (1) only in your first job, (2) also in similar jobs, but with other employers or (3) also in other jobs?' The first type of skills can be classified as being job-specific, the second as transferable, and the last as general skills. The ordered nature of this question implies that answer (3) does not necessarily exclude the acquisition of specific or transferable skills. We can therefore derive the following skill acquisition indicators: the acquisition of any skills (SA-S/T/G), the acquisition of transferable or general skills (SA-T/G), and the acquisition of general skills (SA-G). Green and Montgomery (1998) used similar indicators in their analysis of the specificity of skills that British school-leavers acquired during their first job. A minority (7.8%) of the school leavers in our sample reported acquiring only specific skills in their first job. About one-third also acquired transferable skills (31.3%). This is in line with Stevens (1994), who proposed that many skills are neither completely general nor completely job-specific. Another third even acquired general skills (33.7%).

Table 2 also contains correlations between the different types of training and skill acquisition. The correlation between any training participation (TR) and any skill acquisition (SA-S/T/G) is about 0.22. Each type of training is also positively correlated with skill acquisition, suggesting that the different types of training indeed lead to the acquisition of skills. The learning-by-doing indicator has the highest correlation with skill acquisition, and the learning-by-watching indicator has the lowest. These figures do not change much if we restrict skill acquisition to only general and transferable skills. Further restriction to general skill acquisition alone more than halves the correlation with total training participation. This mainly results from the drop in correlation with the informal training types. This suggests that formal ways of training more often lead to the acquisition of general skills.

We first estimate the reduced form determinants of the three skill acquisition indicators (cf. equation (1.3)), with the same vector of explanatory variables of the training participation analysis (i.e. $\mathbf{X}_i^1 = \mathbf{X}_i^3$). Variables that have a strong impact on one or more types of training participation can be expected to be reduced form determinants of skill acquisition as well. Whether this is indeed the case will depend on the extent to which the different types of training are effective in the production of skills. To investigate this last issue, we also estimate three versions of the skill production function (cf. equation (1.2)). In a first specification, we only include dummies for the five types of training participation. The impact of the different types of training might be largely heterogeneous across different types of workers. Because of complementarities with formal education, for example, some types of training might be more effective for highly-educated school-leavers. Other types of training might serve as a substitute for formal education, so in a second specification, we additionally include interaction terms between the different training dummies and years of education[9]. Differences in volume of training might also explain part of the variation in skill acquisition, so in a third specification, we further include the log of the time spent on learning by doing and on each type of formal training. By taking logs, we take into account that the intensity of the training is likely to be lower among individuals with longer reported training volumes (cf. supra)[10].

The reduced form determinants of skill acquisition are estimated by binary probit models. Both training participation and skill acquisition might be determined by similar unobservables like ability and motivation ($E(\varepsilon_i^{t1}\varepsilon_i^2) \neq 0$), making the five training participation dummies and the three training volume indicators endogenous. To account for endogeneity of the training dummies, we therefore estimate the skill production function by means of a recursive multivariate probit model (cf. Heckman, 1978). More specifically, each specification of the skill production function is estimated simultaneously with the five training participation equations. In our model, identification relies both on the functional form and on the large number of variables that are included in the training participation equations but not in the skill acquisition equation. These exclusion restrictions are based on the assumption that training participation is a prerequisite for the acquisition of new skills[11]. To account for possible endogeneity with respect to three training volume indicators in the last specification, the two-stage conditional maximum likelihood procedure is applied (cf. supra).[12]

IV. The determinants of training participation

In this section, we report the results for the analysis of the determinants of the different types of training (cf. equation (1.1)). Table 3 reports the variance-covariance matrix of the residuals in the multivariate probit and Tobit analyses. The hypothesis that all covariances are equal to zero is rejected for both models. Most covariance estimates of the multivariate probit analysis confirm previous conclusions on the basis of simple bivariate correlations. The two formal training types are found to be complements. Similarly, informal training by a co-worker and learning by watching are also complements. Learning by doing is unrelated to other informal training types but complementary to formal training. Finally, informal training by a co-worker is found to be a substitute for formal on-site training. The covariance of the error terms in the bivariate probit analysis (value = -0.037) is not statistically significant.

"Table 3 here"

In Tables 4 and 5, we report the coefficients and standard errors[13] for the incidence and volume of training. Some explanatory variables are found to have a similar effect on most of the training types as measured in terms of both incidence and volume. The hypothesis that higher-educated workers get more OJT opportunities, for example, is corroborated by most of the estimation results. Although some of the coefficients are not significant at the 10% level, they all have the expected positive sign. For the determinants of training incidence, we find only an insignificant effect on formal on-site training. Moreover, with respect to the volume of training, it is found that higher-educated workers participate in a significantly higher number of formal training courses and have a significantly longer period of learning by doing. Another hypothesis that is largely confirmed is that women have lower training probabilities. On the basis of the aggregate training measure, it is found that women are significantly less likely to be trained than are men. This results from lower incidence rates in all types of training except for TRI-CWS. Additionally, women also have a lower number of formal training courses, a lower volume of formal training time and a shorter period of learning by doing. The hypothesis that temporary contract workers participate less in OJT is clearly established by our results. Only with respect to informal training by a co-worker or supervisor and learning by watching were no significant effects found. In line with expectations too is the greater negative effect from casual or seasonal contracts compared to fixed-term contracts.[14] Finally, white-collar workers are significantly more likely to participate in both formal and informal OJT.[15]

“Table 4 and 5 here”

Other characteristics only have a significant effect on some training types and some training indicators. Having a part-time contract, for example, has a negative impact on formal on-site training participation: the coefficients for training incidence, the volume of training time and the number of courses are all significantly negative. Evidence of a similar relationship with respect to other training types, however, is limited. Although part-time workers are found to have a significantly lower incidence of learning-by-doing training, we do not note a similar result with respect to the duration of the learning-by-doing period. Similarly, those with an employment measurement contract are found to have a significantly lower incidence of informal training, whereas no such outcomes are noted with respect to formal training. Finally, results with respect to tenure and tenure squared are mixed. Nevertheless, some clear patterns can be detected. Clear results are found with respect to the volume of training. In line with theoretical considerations, we find that the investment in training is continuing but declining with tenure. Except for weeks of on-site formal training, all coefficients are statistically significant at the 5% level. With respect to the incidence of training, results differ between formal and informal types of training. The results with respect to formal training are in line with the hypothesis of delayed training investments: the probability of ever having had formal training increases with tenure but at a declining rate. With respect to the incidence of informal training, however, no statistically significant relationship with tenure is detected. Since the provision of formal training is typically more expensive than the provision of informal training, it is not surprising that formal training investments in particular are delayed.

A last group of factors combine a negative impact on participation in one type of training with a positive impact on participation in another. Consequently, no statistically significant effect ($p < 0.05$) is thus noted on participation in any training. The results with respect to firm size and formal training participation are in line with our hypothesis and previous findings in the literature. The incidence, volume and number of formal training courses are all significantly higher in large firms. Moreover, this effect mainly results from higher on-site formal training participation. Workers in large-sized companies are also more likely to be trained informally by co-workers or supervisors than are those in small-size companies. The introduction of learning by watching and learning by doing into the analysis, however, clearly changes this conclusion. Larger firms do not provide more informal training through learning by watching. Additionally, workers in these firms spend far less time in training through learning by doing. Hence, no significant differences in participation in any training are noted between small- and large-sized firms. Given the large number of empirical studies that have found evidence of higher training participation in large firms, this is an interesting result. We also find clear evidence that public sector workers receive more formal on-site training than do private sector workers in terms of both incidence and volume.[16] Still, these higher formal on-site training opportunities are largely compensated by a lower incidence of informal on-site training by a co-worker or supervisor. If evaluated at the 10% level, public sector workers even have a lower incidence of participation in any training. Our results therefore suggest that the private and public sector differ in the type of training that is offered to their employees and not in the quantity of the provided training. Finally, it is often found that non-whites are discriminated in the receipt of OJT. We also note that workers with a non-western background participate less often in formal on-site training. These poorer formal training opportunities appear to be compensated, however, by supplementary informal training such as learning by watching and learning by doing.

This overview clearly illustrates that an analysis on the basis of informal training indicators leads to different conclusions about some of the determinants of skill acquisition in young workers' first jobs. Our findings on participation in formal training, for example, are consistent with the hypothesis of delayed training investments, whereas a similar relation cannot be detected with respect to informal training. Similarly, the higher participation in formal training by large firm or public sector workers is found to be offset by more participation in informal training. Along with their failure to incorporate more informal ways of learning, standard training indicators also have other disadvantages, such as their indirect way of measuring skill acquisition. This last problem is investigated in the next section.

V. The determinants of skill acquisition

In this section, we explore the direct skill acquisition indicators in greater detail. We first analyse reduced form equation (1.3) and investigate whether the differences in training participation between particular groups of workers are mirrored in similar skill acquisition differences. In the second instance, we also study the skills production function (equation (1.2)) and examine the contribution of each type of training to the acquisition of skills.

Table 6 reports the estimation results with respect to reduced form equation (1.3). First, we expect that variables with robust effects in the training participation analysis have a similar impact on skill acquisition. It is indeed found that women, temporary contract workers and blue-collar workers all acquire significantly fewer skills on the job. Furthermore, this leads to a significantly lower probability of these workers' acquiring some general skills. The relatively stronger negative effect in the case of casual or seasonal contracts as compared with fixed-term contracts is also in line with expectations. Finally, we note a significant impact of years of education on any SA and on transferable SA.[17] The skills gap between lower- and higher-educated individuals therefore extends further during the working career. Second, variables such as part-time work, employment measure contracts and tenure were found to have an effect on only some of the training participation indicators. For these variables, this does not lead to significantly different SA probabilities if evaluated at the 5% level. With respect to part-time work and tenure, these outcomes are parallel to those of participation in any type of training. Third, individuals with a non-western background, workers employed in large firms (> 250 employees) and public sector workers combine lower participation in one type of training with higher participation in another. As with participation in any training, no significant effects of these variables on skill acquisition are noted. Thus, the negative impact on skill acquisition from one type of training seems to be offset by the positive effect from another type of training.

"Table 6 here"

Table 7 includes the results with respect to the skills production function (cf. equation (1.2)) on the basis of the recursive multivariate probit models[18]. In a first specification (model (A)), only training incidence dummies are included. As shown in Appendix (A), a majority of the estimated covariances between the residuals of skill acquisition equations and the residuals of the training equations are significantly negative. Hence, those with unmeasured characteristics that result in less skill acquisition seem to be offset by additional training. All types of training are found to be positively related to the acquisition of any type of skills (SA-S/T/G). The size of their impact, however, differs considerably. Informal training by means of learning by doing and formal off-site training are found to have the greatest effect. The impact of informal training by a co-worker or supervisor is estimated to be small and statistically insignificant. The results are relatively similar if the analysis is restricted to transferable or general skills (SA-T/G). For the acquisition of general skills (SA-G), learning by doing is also found to be important. Conversely, the effect of TRF-OFS is now statistically significant, whereas the effect of TRI-CWS becomes statistically significant at the 10% level. These last outcomes are somewhat surprising, since informal training is often thought to be more specific than formal training.

As stated in section II, the efficiency of training activities is likely to differ across individuals. We expect that this individual learning productivity largely depends on the worker's educational background, so in a second specification (model (B)), we include interaction terms of years of education with the different training incidence dummies[19]. Learning by doing is indeed found to be complementary to formal education in the production of all types of skills. Most other types of training, however, seem to work rather as substitutes for formal education; higher educated workers are less likely to learn anything new from formal on-site or off-site training and from informal training by a co-worker or supervisor. The provision of these types of training to highly educated workers therefore seems to be less effective. Among the least educated, conversely, formal types of training are found to have a more pronounced impact on SA than does learning by doing. To assess the total effects of the different types of training on skill acquisition, we computed these effects at the mean values of years of education. As shown in Appendix B, the computed effects are largely similar to those on the basis of model (A).

Individuals with participation in similar types of training can still be quite different with respect to the volume of these types of training. In a third specification (model (C)), we therefore additionally include the total time spent on learning by doing and on each type of formal training. The statistically significant effects of the incidence of formal off-site and learning-by-doing training on SA-S/T/G and SA-S/T in model (B) disappear and are replaced by statistically significant effects of the volume of training. An analogous outcome is noted regarding the relation between formal on-site training and SA-G. Also noteworthy is the fact that the coefficients with respect to TRF-OFS (T) are substantially higher than those with respect to TRF-LBD (T). This seems to confirm that the intensity of learning-by-doing training is lower than the intensity of formal training courses (cf. Section III). As shown in Appendix B, also this specification delivers similar conclusions regarding the total effects of the different types of training[20].

VI. Conclusions

The standard OJT indicators that are typically used in the literature have several flaws. The purpose of this paper was to investigate the consequences of these problems for the analysis of post-school skill acquisition and its determinants. Using unique data regarding first jobs in Flanders, we were able to analyse participation in five types of training (formal off-site, formal on-site, informal co-worker training, learning by watching and learning by doing), and self-assessed skill acquisition.

The first flaw in standard training participation measures concerns their failure to incorporate informal ways of training such as learning by watching and learning by doing. As shown in the paper, formal training is only a fraction of the total amount of training. Whereas some types of informal training are found to be complementary to formal training, others seem to work as substitutes. Accordingly, the determinants of informal and overall training participation are not all equal to those of formal training participation. Three broad categories of determinants can be depicted on the basis of our analysis. A first group of variables has similar effects on most of the training types: less well-educated individuals, women, temporary contract workers and blue-collar workers are generally less likely to participate in training. Other variables such as part-time work, employment measure contracts and tenure only affect a limited number of training indicators. A last group of variables produces opposite effects: workers in small firms, private sector employees and individuals with a non-western background are found to offset less formal training with more informal training.

The indirect approach for the measurement of skill acquisition is also a disadvantage: training indicators measure the time spent on skill formation but don't incorporate the effectiveness of the skill formation process. Thus, we found that the incidence of overall skill acquisition is lower than the incidence of overall training participation. Nonetheless, the worker and job characteristics that explain skill acquisition are largely similar to the determinants of overall training participation. A further examination of the skills formation process revealed that the effectiveness of the provided training largely depends on its type. Learning by doing and formal off-site training appear to be the most effective skills producers. Apart from the type of training, effectiveness also depends on the educational background of the individual worker. A higher level of formal education reduces the benefits of extra formal training but even so reinforces the effect of learning by doing.

Finally, training measures rarely deliver direct information on the transferability of the produced skills. From the point of view of the worker, highly specific skills are less beneficial, since they have no influence on outside labour market opportunities. Only a small minority of the school-leavers in our sample, however, reported that none of the acquired skills were general or transferable to other jobs. Thus, the determinants of transferable skill acquisition were found to be largely similar to those of overall skill acquisition and training participation. It is often assumed that particularly formalised courses lead to the acquisition of skills that are general or transferable to other jobs, whereas informal training contributes to the acquisition of firm- and job-specific skills. This is not, however, the picture that emerges from our results. Learning by doing, particularly in combination with a high level of formal education, is found to have a substantial impact on general skill acquisition.

Our results clearly demonstrate that ignoring the flaws of standard OJT measures might lead to biased conclusions with respect to post-school skill acquisition. Their failure to incorporate more informal ways of training is a particular weakness: these types of training are obviously a major factor in the acquisition of all types of productive skills.

VII. References

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Notes

[1] In the SONAR-surveys, a standard job is defined as a paid job with a standard labour market contract or as self-employment.

[2] The detailed information on training participation is also available for the second and third job. Direct indicators for skill acquisition, however, are lacking for these jobs. With respect to the 1978 cohort, a follow-up survey was conducted at age 26. For the current job (i.e. at age 26), this survey delivers direct measures on skill acquisition but no detailed information on training participation. Those born in 1980 were not questioned at age 26.

[3] A scarce exception is the paper by Arulampalam et al. (2004) on the basis of the European Community Household Panel.

[4] Estimation is based on the Geweke-Hajivassiliou-Keane smooth recursive conditioning simulator. Cappellari and Jenkins (2003) implemented the program in STATA. The number of replications was set at 100, which is substantially larger than the square root of the sample size.

[5] The bivariate Poisson model is estimated by means of the expectation-maximisation algorithm that has been implemented in R by Karlis and Ntzoufras (2005). The standard errors are calculated by 200 bootstrap replications.

[6] For the tobit and Poisson case, see respectively Smith and Blundell (1986) and Wooldridge (1997).

[7] Strictly speaking, the procedure delivers consistent estimates of the original parameters up to a scaling constant, though this is a sufficient condition, since we are not interested in the theoretical values of the parameters.

[8] Models with more than one endogenous variable particularly deliver problems. Estimating our models on the basis of the ivprobit command in STATA 9.0, for example, did not lead to convergence.

[9] Complementary effects might not only prevail between training and formal education but also between the different types of training. With this in mind, we also estimated a specification with an interaction term between the incidence of formal training (TRF (I)) and the incidence of informal training (TRI (I)). Nonetheless, the coefficient on this interaction term was for none of the SA indicators statistically different from zero. These results are not reported but are available upon request.

[10] Estimates whereby SA was estimated as a linear function of the weeks of training resulted in lower log-likelihood values.

[11] Theoretically, these instruments are not required for identification, but misspecification of the functional form is likely to result in poor model performance if exclusion restrictions are absent (Monfardini and Radice, 2008).

[12] The error terms of the three training volume indicators are based on estimations using the same vector of covariates $\mathbf{X}_i^1$ like for the standard training participation analyses.

[13] The included residual terms are treated as observed values, so the reported standard errors are not adjusted. Rivers and Vuong (1988) provide a formula for the adjusted variance-covariance matrix in the binary probit case, but the application of a multivariate model further complicates the computation. With respect to the simple two-stage probit model, there is some Monte Carlo evidence that there is no gain from calculating the more complex standard errors, as these adjusted standard errors are no more effective in large finite samples than the unadjusted standard errors (see Bollen et al., 1995).

[14] The hypothesis that both coefficients are equal is rejected for most of the training indicators. The only indicators for which this hypothesis cannot be rejected are TRI-CWS (I), TRI-LBW (I) and TRI-LBD (T).

[15] This outcome explains the insignificance in some of the estimations of the years of education coefficient. Except for TRF-OFS (T), this coefficient is always significant at the 10% level if the white-collar dummy is excluded as control variable. In line with the hypothesis that education enhances trainability, higher educated workers are thus selected for jobs that require additional training.

[16] Arulampalam et al. (2004) have also found that Belgian public sector workers are significantly more likely to be trained.

[17] Years of education are also found to have a significant effect on SA-G if the white-collar dummy is excluded from the equation. It thus seems that education is helpful for appointment to jobs that require more additional general skills (cf. footnote 13).

[18] To save space, we do not report the results with respect to the training participation equations. In general, these results do not deviate much from the multivariate probit results that are reported in Table 4.

[19] The minimal number of years of education is six years (i.e. primary education). Hence, interaction effects with (*YEDUC-6*) are included instead of with *YEDUC*.

[20] These total effects are computed on the basis of conditional mean values for *LN(1+TRF-OFS (T))*, *LN(1+TRF-ONS (T))* or *LN(1+TRI-LBD (T))*. We base our estimates on mean natural logarithms because of the positive skewness in the training volume distributions.

Table 1: On-the-job training and skill acquisition: Summary statistics

	Incidence (I)	Number of training courses (N)			Weeks of training (T)		
		Mean	Conditional mean	Conditional median	Mean	Conditional mean	Conditional median
TRF-OFS	9.5%	0.17	1.83	1	0.45	4.76	1.00
TRF-ONS	16.9%	0.35	2.05	1	0.80	4.72	1.20
TRI-CWS	33.6%	-	-	-	-	-	-
TRI-LBW	15.4%	-	-	-	-	-	-
TRI-LBD	86.4%	-	-	-	28.22	32.67	24.00
TRF	23.8%	0.52	2.19	1	1.25	5.25	1.40
TRI	92.1%	-	-	-	-	-	-
TR	93.0%	-	-	-	-	-	-
SA-S/T/G	72.8%	-	-	-	-	-	-
SA-T/G	65.0%	-	-	-	-	-	-
SA-G	33.7%	-	-	-	-	-	-

TRF-OFS = formal off-site training, *TRF-ONS*= formal on-site training, *TRI-CWS* = informal training by a co-worker or supervisor, *TRI-LBW* = learning by watching, *TRI-LBD* = learning by doing, *SA-S/T/G* = specific, transferable or general skill acquisition, *SA-T/G* = transferable or general skill acquisition, *SA-G* = general skill acquisition.
Conditional figures are based on individuals with positive training incidence; -: Data not available.
Data source: SONAR 1978 cohort, first job after leaving school, N = 4202.

Table 2: Correlations between the different types of training incidence and skill acquisition

	TRF-OFS (I)	TRF-ONS (I)	TRI-CWS (I)	TRI-LBW (I)	TRI-LBD (I)	TR (I)
TRF-OFS (I)	1.000					
TRF-ONS (I)	0.091***	1.000				
TRI-CWS (I)	-0.008	-0.053***	1.000			
TRI-LBW (I)	0.047***	0.046***	0.218***	1.000		
TRI-LBD (I)	0.088***	0.109***	0.005	0.002	1.000	
SA-S/T/G	0.101***	0.153***	0.090***	0.074***	0.227***	0.218***
SA-T/G	0.103***	0.149***	0.084***	0.078***	0.218***	0.200***
SA-G	0.079***	0.111***	0.036**	0.057***	0.101***	0.097***

TRF-OFS = formal off-site training, *TRF-ONS*= formal on-site training, *TRI-CWS* = informal training by a co-worker or supervisor, *TRI-LBW* = learning by watching, *TRI-LBD* = learning by doing, *SA-S/T/G* = specific, transferable or general skill acquisition, *SA-T/G* = transferable or general skill acquisition, *SA-G* = general skill acquisition.
*:p<0.10; **:p<0.05; ***:p<0.01.

Table 3: Estimated covariances of multivariate probit / Tobit residuals

*Multivariate probit (LR Chi² (10) = 230.77***)*[(#)]	TRF-OFS (I)	TRF-ONS (I)	TRI-CWS (I)	TRI-LBW (I)
TRF-ONS (I)	0.106***			
TRI-CWS (I)	-0.052	-0.231***		
TRI-LBW (I)	0.080*	0.004	0.372***	
TRI-LBD (I)	0.123*	0.109**	0.009	0.023
*Multivariate Tobit (LR Chi² (3) = 11.15**)*[(#)]	TR-OFS (T)	TR-ONS (T)		
TR-ONS (T)	0.003			
TRI-LBD (T)	0.079***	0.042*		

TRF-OFS = formal off-site training, *TRF-ONS*= formal on-site training, *TRI-CWS* = informal training by a co-worker or supervisor, *TRI-LBW* = learning by watching, *TRI-LBD* = learning by doing.

[(#)] Likelihood Ratio test on the null hypothesis that all covariances are equal to zero.

For coefficients and standard errors, see Table 4. *:p<0.10; **:p<0.05; ***:p<0.01.

Table 4: The determinants of training participation incidence: coefficients and standard errors (in parentheses)

	Multivariate probit					Bivariate probit		Probit
	TRF-OFS (I)	TRF-ONS (I)	TRI-CWS (I)	TRI-LBW (I)	TRI-LBD (I)	TRF (I)	TRI (I)	TR (I)
Years of education	0.037*	0.017	0.029**	0.037**	0.091***	0.027*	0.097***	0.100***
	(0.020)	(0.016)	(0.013)	(0.015)	(0.016)	(0.015)	(0.018)	(0.018)
Woman	-0.185***	-0.147**	0.001	-0.111*	-0.383***	-0.189***	-0.366***	-0.459***
	(0.067)	(0.059)	(0.049)	(0.057)	(0.073)	(0.054)	(0.081)	(0.085)
Non-European	-0.079	-0.354**	0.077	0.178*	0.034	-0.229*	-0.027	-0.022
	(0.156)	(0.139)	(0.094)	(0.105)	(0.115)	(0.121)	(0.128)	(0.134)
Part-time job	0.049	-0.273***	-0.091	-0.026	-0.318***	-0.117	-0.218*	-0.221
	(0.105)	(0.097)	(0.076)	(0.090)	(0.116)	(0.085)	(0.129)	(0.136)
Fixed-term contract	-0.241***	-0.296***	-0.030	0.033	-0.379***	-0.301***	-0.303***	-0.283**
	(0.087)	(0.075)	(0.062)	(0.072)	(0.099)	(0.069)	(0.114)	(0.124)
Casual/seasonal contract	-0.607***	-0.660***	-0.126	-0.029	-0.864***	-0.666***	-0.700***	-0.821***
	(0.136)	(0.112)	(0.084)	(0.098)	(0.124)	(0.101)	(0.141)	(0.151)
Employment measure contract	-0.420**	-0.117	0.245*	0.098	-0.698***	-0.200	-0.642***	-0.551**
	(0.214)	(0.155)	(0.138)	(0.157)	(0.199)	(0.149)	(0.221)	(0.242)
White-collar worker	0.214**	0.381***	0.121**	-0.080	1.484***	0.375***	1.314***	1.359***
	(0.092)	(0.078)	(0.062)	(0.074)	(0.094)	(0.071)	(0.109)	(0.117)
Public sector	0.011	0.251***	-0.317***	-0.143	-0.063	0.261***	-0.254	-0.309*
	(0.109)	(0.095)	(0.086)	(0.101)	(0.157)	(0.088)	(0.166)	(0.173)
Firm size 10 - 49	0.030	0.113	0.166***	-0.055	-0.495***	0.059	-0.460***	-0.399***
	(0.085)	(0.078)	(0.060)	(0.071)	(0.092)	(0.070)	(0.105)	(0.108)
Firm size 50 - 249	-0.006	0.392***	0.268***	0.045	-0.575***	0.255***	-0.441***	-0.343***
	(0.092)	(0.081)	(0.064)	(0.075)	(0.098)	(0.073)	(0.112)	(0.116)
Firm size >= 250	0.210**	0.662***	0.268***	-0.010	-0.518***	0.558***	-0.341***	-0.159
	(0.098)	(0.086)	(0.071)	(0.082)	(0.111)	(0.079)	(0.128)	(0.135)
Tenure	0.039**	0.023*	-0.006	-0.012	-0.013	0.042***	-0.013	-0.024
	(0.016)	(0.014)	(0.011)	(0.013)	(0.019)	(0.013)	(0.022)	(0.023)
Tenure²	-0.001**	-0.001**	0.000	0.000	0.000	-0.001***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wald test of exogeneity[(#)]	7.33**	10.17***	3.61	5.45*	2.79	16.48***	4.35	6.96**
Rho			cf. Table 3			-0.037		-
Degrees of freedom			170			68		34
Model LR Chi²			2173.70***			1275.74***		623.23***

TRF-OFS = formal off-site training, *TRF-ONS*= formal on-site training, *TRI-CWS* = informal training by a co-worker or supervisor, *TRI-LBW* = learning by watching, *TRI-LBD* = learning by doing.
Also included but not reported: intercept, dummies for industry (11), region of employment (6), year of birth (1), and residuals from first-step tenure and tenure² OLS estimations (2).
(#): Tests null hypothesis that tenure and tenure² are exogenous; based on joint significance of the residual coefficients; *:p<0.10; **:p<0.05; ***:p<0.01; N=4202.

Table 5: The determinants of training participation volume: coefficients and standard errors (in parentheses)

	Weeks of training					Number of training courses		
	Multivariate Tobit			Bivariate Tobit		Bivariate Poisson		Poisson
	TRF-OFS (T)	TRF-ONS (T)	TRI-LBD (T)	TRF (T)	TRI-LBD (T)	TRF-OFS (N)	TRF-ONS (N)	TRF (N)
Years of education	0.286	0.098	2.152***	0.111	2.152***	0.100***	0.074***	0.077***
	(0.317)	(0.198)	(0.179)	(0.202)	(0.180)	(0.030)	(0.018)	(0.015)
Woman	-2.946***	-2.690***	-4.323***	-3.175***	-4.324***	-0.427***	-0.198***	-0.257***
	(1.114)	(0.706)	(0.669)	(0.723)	(0.672)	(0.085)	(0.063)	(0.049)
Non-European	-1.673	-3.207*	2.790**	-2.719*	2.793**	0.089	-0.399**	-0.279**
	(2.575)	(1.685)	(1.333)	(1.623)	(1.333)	(0.272)	(0.188)	(0.137)
Part-time job	1.294	-2.783**	0.399	-0.713	0.402	0.250*	-0.804***	-0.389***
	(1.711)	(1.196)	(1.020)	(1.148)	(1.020)	(0.139)	(0.127)	(0.094)
Fixed-term contract	-5.214***	-3.463***	0.464	-4.605***	0.467	-0.383***	-0.449***	-0.444***
	(1.452)	(0.899)	(0.854)	(0.922)	(0.852)	(0.133)	(0.092)	(0.069)
Casual/seasonal contract	-11.435***	-7.012***	-0.838	-8.936***	-0.838	-1.184***	-1.333***	-1.337***
	(2.322)	(1.375)	(1.170)	(1.397)	(1.173)	(0.235)	(0.148)	(0.126)
Employment measure contract	-8.014**	-2.541	-2.305	-4.432**	-2.299	0.091	-0.509***	-0.329**
	(3.584)	(1.860)	(1.941)	(1.983)	(1.949)	(0.230)	(0.149)	(0.135)
White-collar	3.230**	5.196***	13.431***	5.210***	13.431***	0.492***	0.508***	0.508***
	(1.520)	(0.951)	(0.861)	(0.966)	(0.865)	(0.140)	(0.097)	(0.076)
Public sector	1.053	3.519***	-1.117	4.007***	-1.116	0.077	0.174*	0.131*
	(1.827)	(1.139)	(1.135)	(1.172)	(1.135)	(0.138)	(0.094)	(0.078)
Firm size 10 - 49	-0.958	0.489	-2.801***	-0.655	-2.801***	-0.271**	-0.053	-0.116*
	(1.398)	(0.957)	(0.815)	(0.940)	(0.816)	(0.117)	(0.090)	(0.069)
Firm size 50 - 249	0.233	3.287***	-4.406***	2.344**	-4.406***	-0.414***	0.215**	0.007
	(1.493)	(0.985)	(0.878)	(0.978)	(0.882)	(0.124)	(0.091)	(0.072)
Firm size >= 250	2.581	7.345***	-3.399***	6.480***	-3.400***	0.140	0.687***	0.509***
	(1.609)	(1.042)	(0.977)	(1.047)	(0.978)	(0.131)	(0.094)	(0.071)
Tenure	0.648**	0.212	3.516***	0.474***	3.516***	0.141***	0.068***	0.083***
	(0.273)	(0.171)	(0.154)	(0.173)	(0.154)	(0.025)	(0.017)	(0.014)
Tenure²	-0.015***	-0.003	-0.049***	-0.009***	-0.049***	-0.003***	-0.002***	-0.002***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.000)	(0.000)
Wald test of exogeneity[(#)]	9.70***	4.01	42.56***	10.86***	42.50***	13.09***	34.58***	52.30***
Rho (Tobit) / Lambda (Poiss.)		cf. Table 3		0.066***		0.008***		-
Degrees of freedom		102		68		68		34
Model LR Chi²		3758.03***		3594.25***		2000.31***		1835.95***

TRF-OFS = formal off-site training, *TRF-ONS*= formal on-site training, *TRI-LBD* = learning by doing. [(#)]: Tests null hypothesis that tenure and tenure² are exogenous; based on joint significance of the residual coefficients.
*: p<0.10; **:p<0.05; ***: p<0.01; N=4202. Also included but not reported: cf. Table 4.

Table 6: The determinants of skill acquisition and its transferability: coefficients and standard errors (in parentheses)

	Binary Probit		
	SA-S/T/G	SA-S/T	SA-G
Years of education	0.051*** (0.013)	0.051*** (0.013)	0.012 (0.013)
Woman	-0.381*** (0.052)	-0.261*** (0.049)	-0.158*** (0.048)
Non-European	0.074 (0.098)	0.068 (0.094)	-0.144 (0.099)
Part-time job	-0.057 (0.076)	-0.107 (0.073)	-0.137* (0.074)
Fixed-term contract	-0.201*** (0.066)	-0.232*** (0.063)	-0.166*** (0.062)
Casual/seasonal contract	-0.481*** (0.087)	-0.572*** (0.084)	-0.389*** (0.085)
Employment measure contract	-0.287* (0.147)	-0.177 (0.142)	-0.110 (0.140)
White-collar worker	0.261*** (0.065)	0.280*** (0.062)	0.327*** (0.063)
Public Sector	-0.031 (0.089)	-0.087 (0.084)	0.010 (0.082)
Firm size 10 - 49	-0.121* (0.062)	-0.054 (0.059)	-0.006 (0.060)
Firm size 50 – 249	-0.073 (0.068)	0.054 (0.065)	0.112* (0.064)
Firm size >= 250	0.048 (0.077)	-0.006 (0.072)	0.063 (0.071)
Tenure	0.016 (0.012)	0.001 (0.011)	-0.013 (0.011)
Tenure²	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Wald test of exogeneity(#)	9.45***	21.25***	16.07***
Model LR Chi² (34)	486.22***	457.58***	219.24***

SA-S/T/G = specific, transferable or general skill acquisition, *SA-T/G* = transferable or general skill acquisition, *SA-G* = general skill acquisition.
(#): Tests null hypothesis that tenure and tenure² are exogenous; based on joint significance of the residual coefficients.
*: p<0.10; **:p<0.05; ***: p<0.01; N=4202.
Also included but not reported: cf.Table 4.

Table 7: The impact of training participation on skill acquisition: coefficients and standard errors (in parentheses) on the basis of recursive multivariate probit models(#)

	(A)			(B)			(C)		
	SA-S/T/G	SA-T/G	SA-G	SA-S/T/G	SA-T/G	SA-G	SA-S/T/G	SA-T/G	SA-G
TRF-OFS (I)	1.373*** (0.163)	1.209*** (0.177)	0.416 (0.321)	1.796*** (0.277)	1.788*** (0.306)	0.816* (0.469)	-0.353 (0.776)	-0.579 (0.595)	0.621 (0.529)
TRF-ONS (I)	0.763*** (0.180)	0.658*** (0.183)	0.353* (0.196)	1.300*** (0.267)	1.011*** (0.282)	0.490* (0.290)	1.231*** (0.387)	1.196*** (0.352)	-0.555* (0.315)
TRI-CWS (I)	0.033 (0.235)	0.091 (0.230)	0.454* (0.243)	0.390 (0.249)	0.478* (0.270)	0.893*** (0.279)	-0.139 (0.264)	0.042 (0.266)	0.853*** (0.230)
TRI-LBW (I)	0.698*** (0.229)	0.283 (0.287)	0.549* (0.296)	0.960*** (0.273)	0.304 (0.368)	0.265 (0.378)	0.697* (0.401)	0.257 (0.367)	-0.095 (0.350)
TRI-LBD (I)	1.010*** (0.112)	1.190*** (0.103)	0.846*** (0.099)	0.798*** (0.151)	0.674*** (0.153)	0.370** (0.160)	-0.180 (0.218)	-0.181 (0.200)	0.009 (0.191)
TRF-OFS (I)*(YEDUC-6)	-	-	-	-0.051* (0.030)	-0.070** (0.032)	-0.054* (0.032)	-0.006 (0.038)	-0.026 (0.033)	-0.048 (0.031)
TRF-ONS (I)*(YEDUC-6)	-	-	-	-0.077*** (0.028)	-0.063** (0.027)	-0.028 (0.026)	-0.079** (0.032)	-0.065** (0.028)	-0.016 (0.024)
TRI-CWS (I)*(YEDUC-6)	-	-	-	-0.041** (0.018)	-0.039** (0.018)	-0.048*** (0.018)	-0.040** (0.019)	-0.037** (0.019)	-0.047*** (0.018)
TRI-LBW (I)*(YEDUC-6)	-	-	-	-0.029 (0.024)	-0.010 (0.025)	0.028 (0.025)	-0.021 (0.026)	-0.005 (0.025)	0.029 (0.024)
TRI-LBD (I)*(YEDUC-6)	-	-	-	0.028** (0.013)	0.065*** (0.013)	0.057*** (0.014)	0.045*** (0.014)	0.078*** (0.014)	0.067*** (0.014)
LN(1+TRF-OFS (T))	-	-	-	-	-	-	2.031*** (0.572)	1.932*** (0.520)	0.099 (0.537)
LN(1+TRF-ONS (T))	-	-	-	-	-	-	0.030 (0.231)	-0.260 (0.199)	0.792*** (0.194)
LN(1+TRI-LBD (T))	-	-	-	-	-	-	0.217*** (0.060)	0.176*** (0.055)	0.036 (0.055)
Degrees of Freedom	175	175	175	180	180	180	186	186	186
Wald Chi²	2792.23***	2686.43***	2091.96***	2881.29***	2611.98***	2044.58***	2374.51***	2401.15***	1968.98***

(#) Estimation results on the basis of a recursive multivariate probit model where the impact of the different training dummies is estimated simultaneously with the determinants of the different types of training. For the estimated covariances between the error terms of the SA equations and the training equations, see Appendix A.
Also included but not reported: intercept (model (A), (B) and (C)), and residuals from first step LN(1+TRF-OFS (T)), LN(1+TRF-ONS (T) and LN(1+TRI-LBD (T)) linear regression estimates (model (C)); *YEDUC* = years of education, *TRF-OFS* = formal off-site training, *TRF-ONS*= formal on-site training, *TRI-CWS* = informal training by a co-worker or supervisor, *TRI-LBW* = learning by watching, *TRI-LBD* = learning by doing, *SA-S/T/G* = specific, transferable or general skill acquisition, *SA-T/G* = transferable or general skill acquisition, *SA-G* = general skill acquisition; *: p<0.10; **:p<0.05; ***: p<0.01; N=4202.

Appendix A: Estimated covariances of the recursive multivariate probit residuals

	(A)			(B)			(C)		
	SA-S/T/G	SA-T/G	SA-G	SA-S/T/G	SA-T/G	SA-G	SA-S/T/G	SA-T/G	SA-G
TRF-OFS (I)	-0.683***	-0.563***	-0.138	-0.723***	-0.603***	-0.132	0.241	0.439*	-0.034
TRF-ONS (I)	-0.288**	-0.231**	-0.070	-0.280***	-0.164	-0.017	-0.336**	-0.305**	0.507***
TRI-CWS (I)	0.092	0.081	-0.277*	0.034	0.005	-0.338**	0.375***	0.267**	-0.337***
TRI-LBW (I)	-0.286**	-0.050	-0.294**	-0.337***	-0.033	-0.252	-0.098	0.068	-0.057
TRI-LBD (I)	-0.379***	-0.500***	-0.446***	-0.340***	-0.399***	-0.344***	-0.303**	-0.377***	-0.331***

TRF-OFS = formal off-site training, *TRF-ONS*= formal on-site training, *TRI-CWS* = informal training by a co-worker or supervisor, *TRI-LBW* = learning by watching, *TRI-LBD* = learning by doing, *SA-S/T/G* = specific, transferable or general skill acquisition, *SA-T/G* = transferable or general skill acquisition, *SA-G* = general skill acquisition;
For coefficients and standard errors of the SA equations: see Table 7; *: p<0.10; **:p<0.05; ***: p<0.01.

Appendix B: Estimated discrete effects of the different types of training on the probability to acquire new skills[(#)]

	(A)			(B)			(C)		
	SA-S/T/G	SA-T/G	SA-G	SA-S/T/G	SA-T/G	SA-G	SA-S/T/G	SA-T/G	SA-G
TRF-OFS (I)	0.508	0.432	0.075	0.531	0.475	0.087	0.545	0.470	0.098
TRF-ONS (I)	0.286	0.215	0.061	0.289	0.189	0.053	0.284	0.172	0.049
TRI-CWS (I)	0.011	0.024	0.084	0.035	0.062	0.118	-0.142	-0.066	0.138
TRI-LBW (I)	0.260	0.082	0.107	0.284	0.068	0.088	0.219	0.079	0.022
TRI-LBD (I)	0.382	0.424	0.195	0.373	0.401	0.176	0.322	0.355	0.155

[(#)] Based on estimates reported in Table 7; These effects are computed for individuals with no participation in any of the other types of training, mean years of education (model (B) and (C)), and conditional mean values for *LN(1+TRF-OFS (T))*, *LN(1+TRF-ONS (T))* or *LN(1+TRI-LBD (T))* (model (C)).
TRF-OFS = formal off-site training, *TRF-ONS*= formal on-site training, *TRI-CWS* = informal training by a co-worker or supervisor, *TRI-LBW* = learning by watching, *TRI-LBD* = learning by doing, *SA-S/T/G* = specific, transferable or general skill acquisition, *SA-T/G* = transferable or general skill acquisition, *SA-G* = general skill acquisition.